INDUSTRY MARKET VALUE AT RISK IN AUSTRALIA

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Abstract

Value at Risk (VaR) is an important issue for banks since its adoption as a primary risk metric in the Basel Accords and the requirement that it is calculated on a daily basis. Relative industry risk measurement is also very important to Banks in their management of risk, such as for setting risk concentration limits and developing investment and credit policy. This paper examines market Value at Risk (VaR) and Conditional VaR (CVaR) in Australia from an industry perspective using a set of Australian industries. VaR and CVaR are compared between these industries over time, and a variety of metrics are used including diversified and undiversified VaR, as well as parametric and nonparametric CVaR methods. There has been no prior investigation of industry based VaR metrics in Australia to the authors' knowledge. The relative riskiness of different industry sectors is examined and using diversified VaR, the study finds the highest risk is in the Technology Sectors, whilst the lowest risk is found in the Finance and Utilities Sectors. Composite riskiness is also explored and the existence of correlation between industry risk rankings over time is found to depend on the number of years of data used. There is evidence of rank correlation over time using a 7 year window approach, but not when using 1 year data tranches. This highlights the importance of using both short and long time frames in order to cover different economic cycles as well as consider current conditions.

It is important to note that there is found to be no significant difference between diversified and undiversified industry VaR rankings, or between parametric and nonparametric CVaR approaches. This means that bankers can be reasonably confident of the robustness of any one of these metrics when calculating and applying them, not only for the purposes of Basel compliance, but also for the determination of relative industry risk.

Key words: Conditional Value at Risk (CVaR), Industry Risk, Basel Compliance

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Introduction

VaR models have gained increasing momentum since the VaR concept was first introduced by JP Morgan in 1994. This momentum was spurred by amendments to the Basel Accord in 1996 which required Banks to set aside capital for meeting Market Risk. Market risk arises from factors that affect the whole market. This paper focuses on equities and compares relative VaR and CVaR across 25 Australian industries, based on equity price movements using a parametric distribution, which is the most widely used approach among Banks. VaR has become the recognised standard approach for market risk measurement. VaR calculates maximum expected losses over a given time period at a given tolerance level.

In addition to VaR, this paper examines extreme industry risk using (conditional) CVaR. CVaR considers extreme events, based on losses exceeding VaR. Whilst there have been a wide range of VaR studies in USA and European markets, the vast majority have centred around individual asset or overall portfolio VaR as opposed to adopting a sectoral approach. There is very little study of industry risk using VaR approaches in the Australian market, and even less on CVaR. Indeed, very little research has been undertaken on the uses and applications of VaR or related metrics at all in Australia. (A search of APRA's website at http://www.apra.gov.au /RePEc/Home .cfm?FormStatus =Sent&TargetSeries= Working%20Papers:RePEc:apr:aprewp revealed Sy (2006), Engel and Gizycki (1999) and Gizycki and Hereford (1999) as being the only papers considering aspects of VaR).

This paper aims to provide a greater understanding of the VaR and CVaR modelling approaches, as well as industry risk, in an Australian context. Industry market VaR is measured for each industry in Australia based on the variance-covariance parametric model, using both diversified and undiversified approaches. CVaR is measured using both parametric and nonparametric methodology. The study also compares VaR and CVaR changes between industries over time.

The paper provides background to the Australian Market, a discussion on VaR and CVaR approaches, an outline of methodology used, and then presents the results and conclusions. This comprehensive exploration and application of these various VaR metrics should indicate whether the measures are robust and consistent over time and across industry sectors. The paper is divided into eight sections: section two provides a brief review of the Australian equities market whilst section three reviews the concept of VaR and section four that of CVaR. Section five reviews the data used and the research method, and the analysis is presented in section six. Section seven presents the results from the viewpoint of industrial sectors and section eight concludes.

2 The Australian Market

There has been significant recent growth in the Australian Equities Market. In 1992, the Australian domestic market capitalisation was $198 billion, and this has since grown to $1.4 trillion. Appendix 1 shows the sector and sub sector classifications used by the Australian Stock Exchange (ASX). These sectors are based on the Global Industry Classification Standard (GICS) which is a joint Standard & Poor's / Morgan Stanley Capital International Product aimed at standardising global industry classifications.

The S&P/ASX 200 is recognised as the investable benchmark for the Australian equity market and comprises 200 stocks selected by the S&P Australian Index Committee and represents approximately 90% of the total market capitalisation of the Australian Market (Standard & Poor's, 2006, p.1). The All Ordinaries index (All Ords) is considered to be Australia's market indicator, representing the 500 largest companies listed on the stock exchange (Standard & Poor's, 2006, p.1), and is the index used in this paper. Appendix 2 provides a breakdown of the market capitalisation of All Ords companies.

3 Value at Risk

The use of VaR has become all-pervasive in a relatively short period of time despite its conceptual and practical shortcomings. VaR received its first broad recommendation in the 1993 Group of Thirty Report. Subsequently its use and recognition have increased dramatically, particularly when the Basel Committee on Banking Supervision adopted the use of VaR models, contingent upon certain qualitative and quantitative standards. VaR has subsequently become one of the most important and widely used measures of risk. As a risk-management technique VaR describes the loss that can occur over a given period, at a given confidence level, due to exposure to market risk. The appealing simplicity of the VaR concept has lead to its adoption as a standard risk measure for financial entities involved in large scale trading operations, but also retail banks, insurance companies, institutional investors, and non-financial enterprises. Its use is encouraged by the Bank for International Settlements, the American Federal Reserve Bank and the Securities and Exchange Commission.

The groundbreaking Basel Capital Accord, originally signed by the Group of Ten (G10) countries in 1988, but since largely adopted by over 100 countries, requires Authorised Deposit-taking Institutions (ADI's) to hold sufficient capital to provide a cushion against unexpected losses. Value-at-Risk (VaR) is a procedure designed to forecast the maximum expected loss over a target horizon, given a (statistical) confidence limit. Initially, the Basel Accord stipulated a standardized approach which all institutions were required to adopt in calculating their VaR thresholds. This approach suffered from several deficiencies, the most notable of which were its conservatism (or lost opportunities) and its failure to reward institutions with superior risk management expertise.

Following much industry criticism, the Basel Accord was amended in April 1995 to allow institutions to use internal models to determine their VaR and the required capital charges. However, institutions wishing to use their own models are required to have the internal models evaluated by the regulators using the back-testing procedure. The Basel Accord (BA) was adopted by the Australian government in 1988, with the Australian Prudential Regulatory Authority (APRA) as the national regulator of financial markets. According to APRA, Australia is now fully compliant with 11 BA principles, largely compliant with 12, and materially non-compliant with 2. Importantly, Australia is compliant with Principle 12, which states that:

"Banking supervisors must be satisfied that banks have in place systems that accurately measure, monitor and adequately control market risk; supervisors should have the powers to impose specific limits and/or a specific capital charge on market risk exposures, if warranted."

A description of the various methodologies for the modelling of VaR can be seen at http://www.gloriamundi.org/ . The predominant approaches to calculating VaR rely on a linear approximation of the portfolio risks and assume a joint normal (or log-normal) distribution of the underlying market processes. There is a comprehensive survey of the concept by Duffie and Pan (1997), and discussions in Jorion (1996), Pritsker (1997), RiskMetricsTM (1996), Beder (1995), and Stambaugh (1996).

Despite its universal adoption and promotion by the regulatory authorities and its embrace by the financial services industry there are a number of theoretical and practical difficulties associated with the use of VaR as a risk metric. A standard procedure, in terms of the practical implementation of VaR metrics, if the portfolio of concern contains non-linear instruments such as options, is to make recourse to historical or Monte-Carlo simulation based tools. See the discussions in Bucay and Rosen (1999), Jorion (1996), Mauser and Rosen (1999), Pritsker (1997), RiskMetricsTM (1996), Beder (1995) and Stambaugh (1996). The optimisation problems associated with calculating VaR are discussed in papers by Litterman, (1997a, and 1997b), Kast et al (1998), and Lucas and Klaussen (1998).

Nevertheless, despite its popularity, VaR has certain undesirable mathematical properties; such as lack of sub-additivity and convexity; see the discussion in Arztner et al (1997, 1999). In the case of the standard normal distribution VaR is proportional to the standard deviation and is coherent when based on this distribution but not in other circumstances. The VaR resulting from the combination of two portfolios can be greater than the sum of the risks of the individual portfolios. A further complication is associated with the fact that VaR is difficult to optimize when calculated from scenarios. It can be difficult to resolve as a function of a portfolio position and can exhibit multiple local extrema, which makes it problematic to determine the optimal mix of positions and the VaR of a particular mix. See the discussion of this in Mckay and Keefer (1996) and Mauser and Rosen (1999).

This paper features the exploration and application of an alternative to VaR: CVaR – Conditional-Value-at-Risk. Pflug (2000) proved that CVaR is a coherent risk measure with a number of desirable properties such as convexity and monotonicity w.r.t stochastic dominance of order 1, amongst other desirable characteristics. Furthermore, VaR gives no indication on the extent of the losses that might be encountered beyond the threshold amount suggested by the measure. By contrast CVaR does quantify the losses that might be encountered in the tail of the distribution. This is because a portfolio's CVaR is the loss one expects to suffer, given that the loss is equal to or larger than its VaR. A number of recent papers apply CVaR to portfolio optimization problems; see for example Rockafeller and Uryasev (1999, and 2002), Alexander et al (2003), Alexander and Baptista (2003), Rockafellar et al (2004). However, there has been no prior use or application of CVaR in an Australian setting and its use, properties and applications are still in the early stages of their development.

VaR calculates maximum expected losses over a given time period at a given tolerance level. There are 3 methods of calculating VaR. The Variance-Covariance method estimates VaR on assumption of a normal distribution. The historical method groups historical losses in categories from best to worst and calculates VaR on the assumption of history repeating itself. The Monte Carlo method simulates multiple random scenarios.

The Variance-Covariance approach is the most widely used approach, and is the method we use in this study. To obtain VaR for a single asset X, all that needs to be calculated is the mean and standard deviation. Using standard distribution tables, and given the normal curve assumption, we know where the worst 1% and 5% lie on the curve. VaR at 95% confidence level = 1.645 x 1a1x and at 99% confidence level = 2.330 x 1a1x. When calculating VaR, it is usual practice to not use actual asset figures, but the logarithm of the ratio of price relatives, which is the method used by RiskMetrics (J.P. Morgan & Reuters, 1996, p.p.45-48). This is obtained by using the following calculation:

$$\ln\left(\frac{p_t}{p_{t-1}}\right)$$

i.e. the logarithm of the ratio between today's price and the previous price. The standard deviation is annualised by multiplying it by the square root of the number of trading days per annum (usually taken to be 250).

When additional assets are introduced into the portfolio, we need to account for correlations between the assets. Portfolio variance is calculated as follows, with w being the relative weighting of the assets:

$$V_{port} = w_x^2\sigma_x^2 + w_y^2\sigma_y^2 + 2w_x w_y \sigma_x^2\sigma_y^2\rho_{xy}$$

When dealing with multiple assets, variance-covariance matrix multiplication is used. The portfolio standard deviation is the square root of the variance multiplied by the square root of 250.

4 Conditional Value-at-Risk

CVaR is closely related to VaR. CVaR is equal or greater than VaR. It is the conditional expected loss under the condition it exceeds VaR. CVaR is also called mean excess loss, mean shortfall, or tail VaR. 3b2-VaR is a value with probability 3b2 the loss will not exceed 3b2-VaR. CVaR is the mean value of the worst (1- 3b2)*100% losses. For instance, if we are measuring VaR at a 95% confidence level (3b2=0.95), CVaR is the average of the 5% worst losses. (Uryasev & Rockafellar, 1999, p.p.1-2). CVaR can be calculated using the actual 5% worst losses (nonparametric). CVaR can also be calculated using a normal distribution (parametric) approach, as follows (Huang, 2000)

$$CVAR_\alpha = \frac{\exp(-\frac{q_\alpha^2}{2})}{\alpha\sqrt{2\pi}}\sigma$$

Where q_α is the tail 100_α percentile of the standard normal distribution (e.g. 1.645 as obtained from standard distribution tables for 95% confidence).

5 Methodology

5.1 Data

We use the All Ords and obtain daily share prices for the last 15 years (which is the maximum available) from Datastream. For market VaR, Basel requires 250 days data. This is only 1 year, and we are more concerned with a longer term perspective, spanning different economic conditions. It should be noted at this stage that this paper is a summary of the market VaR section of a wider study which also includes Credit VaR. This wider study compares VaR between credit models and market models to ascertain whether there is a correlation between the industries that are risky from a credit perspective and those that are risky from a market perspective. The study follows the Basel requirement for 7 years data for the advanced credit approach (Bank for International Settlements, 2004, p.98). For comparison purposes, and to meet our requirement for longer market perspectives, we also use 7 year windows for calculating market VaR. This allows 9 years of comparative data (the first tranche being years 1-7, second tranche years 2-8, and so on until the 9th tranche which represents the 7 years from 9 – 15 of our data sample). We recognise that the longer sample may have different results to a shorter sample, and so we also do an historical comparison using 250 day windows. Industry codes are obtained from the ASX website and Market Capitalisation (for weighting of market VaR company data) is obtained from Datastream.

5.2 Data Limitations & Considerations

The data poses some limitations & considerations, such as the fact that the industry classifications used by Datastream are different from those used by the ASX, and that some industries have very few entities from which to make meaningful conclusions. The balance of this section outlines some of these issues and how we overcome them.

5.2.1 Sector accuracy, classification and size

Datastream uses the UK FTSE industry classifications. To ensure accuracy of classification, and to align with what is actually used on the ASX and by Moody's and Standard & Poor's, all companies in this study have been re-classified to GICS. This is done by obtaining individual GICS codes for each entity from the ASX website. To ensure a meaningful quantity of data, Sectors with less than 5 companies, and companies with less than 12 months data have been excluded. The remaining companies represent 93% of those in the All Ords Index by both number and market capitalisation. As the All Ords represent more than 90% of the value of listed Australian companies, we consider 5 entities to be sufficient to provide meaningful conclusions.

5.2.2 Survivorship bias

This occurs when an index only includes current surviving companies and excludes failed entities (Brailsford & Heaney, 1998, p.229). This may cause a favourable bias in the results. An index such as the All Ords (and all other indices on the ASX) will not include failed companies as these would have been delisted. We are not be able to include all failed companies over the 15 years as the historical data for all of these is not available on Datastream. We were however able to obtain Datastream data for companies placed in administration or receivership and delisted over the past 3 years. This amounts to 11 companies, spanning 7 industries. To test for the impact of survivorship bias we ran our model with these companies included in our first rolling window and compared the industry VaR rankings including failed companies to the results excluding failed companies, testing for significance using the Spearman Rank Correlation Test (refer Section 5.5). Changes were found to be not significant at the 95% level and we therefore consider survivorship bias not to have a significant impact on our study.

5.2.3 Thin trading

This problem occurs when infrequently traded companies are included in a time series analysis. Brailsford & Heaney (1998, p.p. 239-244) describe the effect as being most prominent in using daily share price data, but can also exist when using weekly or monthly data. Liquid (highly traded) assets are continually re-pricing based on market information. When thinly traded asset prices do change, they incorporate all the market information since the last trade.

This study uses daily price data as less frequent data does not capture the intervening volatility. A share could start and finish the week on the same price, but have experienced several up and down daily movements. In particular, it is important for the CVaR measure to incorporate all extreme price movements. This does give rise to potential thin trading problems. This can be reduced by avoiding thinly traded assets. In our case we are using the All Ords index which consists of the top 500 companies on the ASX, thus avoiding the most thinly traded assets. We further account for thin trading by applying an adjustment factor as proposed by Miller, Muthuswamy, and Whaley (1994, p.p.479-513) who suggest that a Moving Average model reflecting the number of non-trading days should be used to adjust returns. Due to difficulty in identifying non trading days, the approach shows that this is equivalent to estimating an AR (1) model from which the required adjustment can be determined. Their model involves the following regression equation:

$$R_t = a_1 + a_2 R_{t-1} + \epsilon_t$$

The residual is then used to calculate the adjusted return as follows:

$$R_t^{adj} = \frac{\epsilon_t}{(1-a_2)}$$

Where R_t^{adj} = the return at time t with thin trading adjustment.

5.2.4 VaR Calculation

We calculated VaR using the methodology described in Section 3. We begin by calculating the standard deviation of the logarithm of the daily price relatives. Weightings are calculated for each company according to market capitalisation. Undiversified VaR is obtained by multiplying the weighted undiversified standard deviation by 1.645 (as obtained from standard normal distribution tables for 95% confidence level). Diversified VaR is obtained through construction of a weighted variance-covariance matrix for each rolling 7 year period, and multiplying the portfolio standard deviation by 1.645. Both undiversified VaR and diversified VaR are annualised by multiplying by the square root of 250.

5.3 CVaR calculation

We use a parametric approach to calculate VaR, therefore intuitively it makes sense to use this approach for CVaR. However this approach has some limitations. It will yield a ranking spread for CVaR that is the same as VaR, which may not highlight the extreme returns. We therefore use both parametric and nonparametric approaches.

We use equation 4.1 to calculate parametric CVaR. As we have calculated VaR based on a 95% confidence level, CVaR is based on the worst 5% of losses. Nonparametric CVaR is calculated as the weighted average of returns beyond VaR.

5.4 Testing for significance

Hypotheses were formulated for the objectives outlined in Section 1. We used nonparametric testing, as this is particularly suitable for testing ranking and for smaller data samples (we have 25 industries and 9 time periods). The Pearson Rank Correlation Test to was used test for ranking association between diversified and undiversified VaR, VaR and CVaR, parametric and nonparametric CVaR. The Kruksal-Wallis Test was used to test for ranking association over time. The details of these testing methods is beyond the scope of this paper but can be found in statistical textbooks such as Siegel & Castellan (1988,p.p. 206-244) and Lee, Lee & Lee (2000, p.p.759-784). Suffice it to say that each test compares the rankings and arrives at a test statistic (t for Spearman Rank Correlation, and K for Kruksal-Wallis) which is compared to a critical value for the level of significance being tested (in our case 95%).

6 Results

6.1 Overall Summary

Table 1 shows the VaR calculated on both a diversified and undiversified basis. The undiversified approach being the weighted average of all the individual company VaRs and the diversified approach including the correlation of all the entities in the industry with each other. It should be noted that the table only includes the most recent 7 year rolling window. Historical data is discussed in Sections 6.2 and 6.5

CVaR is obtained using both the parametric approach and the nonparametric approach. The parametric approach uses equation 4.1 and the nonparametric approach is calculated as the weighted average of the actual returns beyond VaR.

Table 1

VaR Calculated on a diversified and non-diversified basis

The model rates the technology sectors as having the highest risk, with Technology Hardware & Equipment and Software & Services having the highest VaR scores. This is not surprising given the well known high volatility experienced in the technology sector over the past 7 years. Also ranked in the top undiversified risk quartile are Pharmaceuticals & Biotechnology, Paper & Forest Products, Energy, and Metals & Mining.

Lowest undiversified risk ranking is accorded to the Banking Sector. This is followed by Telecommunications, Food & Staples Retailing, Utilities, Real Estate, and Food, Beverage & Tobacco.

The results generally tend to show a lower VaR in essential / staple industries (e.g. food & beverage, staples retailing, utilities, banking) as opposed to discretionary and high technology ones (e.g. software, technology hardware, other retailing). There is a noticeable reduction in VaR when using the diversified approach, with the weighted average VaR dropping from 45.16% to 26.75%. The impact of diversification is further discussed in Section 6.3.

A study undertaken by Harper (2004, p.4) in the U.S., using 10 year data, showed the S&P 500 to have an annualised standard deviation of 18.1% and the Nasdaq 28.8%. This equates to VaR of 29.8% and 47.4% respectively at the 95% confidence level. Our portfolio has a diversified VaR of 26.75%, which is fairly similar to the S&P 500, and the higher VaR experienced by

Industry	Number of Companies	Aggregate Market Capitalisation $m	Undiversified Standard Deviation	Annual Undiversified 95% VaR	Diversified Standard Deviation	Diversified Portfolio 95% VaR	Daily Undiversified VaR	Parametric CVaR	Nonparametric CVaR
Automobiles & Components	5	940	0.3293	0.5417	0.1830	0.3010	0.0343	0.0430	0.0536
Banks	13	238684	0.1842	0.3030	0.1356	0.2231	0.0192	0.0240	0.0268
Capital Goods	27	29655	0.2791	0.4591	0.1440	0.2369	0.0290	0.0364	0.0428
Chemicals	6	10623	0.2562	0.4215	0.1888	0.3106	0.0267	0.0334	0.0396
Commercial Services & Supplies	26	30875	0.3271	0.5380	0.1473	0.2424	0.0340	0.0427	0.0530
Construction Materials	5	26321	0.2689	0.4424	0.1943	0.3196	0.0280	0.0351	0.0390
Consumer Durables & Apparel	7	4301	0.3218	0.5294	0.2371	0.3901	0.0335	0.0420	0.0506
Diversified Financials	40	51828	0.2520	0.4145	0.1221	0.2008	0.0262	0.0329	0.0392
Energy	34	80045	0.3589	0.5904	0.1737	0.2858	0.0373	0.0468	0.0538
Food & Staples Retailing	6	44120	0.2266	0.3727	0.1495	0.2459	0.0236	0.0295	0.0343
Food Beverage & Tobacco	15	26734	0.2424	0.3987	0.1229	0.2022	0.0252	0.0316	0.0369
Healthcare Equipment & Services	17	16099	0.3189	0.5246	0.1382	0.2273	0.0332	0.0416	0.0499
Hotels Restaurants & Leisure	10	20165	0.3129	0.5147	0.1914	0.3148	0.0326	0.0408	0.0510
Insurance	7	58985	0.3262	0.5366	0.2052	0.3376	0.0339	0.0425	0.0586
Media	18	32306	0.2773	0.4561	0.1409	0.2317	0.0288	0.0362	0.0417
Metals & Mining	64	207728	0.3401	0.5595	0.2056	0.3382	0.0354	0.0444	0.0498
Paper & Forest Products	8	5373	0.4081	0.6713	0.2196	0.3612	0.0425	0.0532	0.0653
Pharmaceuticals & Biotechnology	23	16993	0.4091	0.6729	0.2262	0.3721	0.0426	0.0534	0.0656
Real Estate	54	115324	0.2390	0.3931	0.1124	0.1850	0.0249	0.0312	0.0381
Retailing	20	9535	0.3086	0.5077	0.1715	0.2821	0.0321	0.0403	0.0469
Software & Services	18	8845	0.5114	0.8412	0.2646	0.4353	0.0532	0.0667	0.0862
Technology Hardware & Equipment	9	1944	0.5784	0.9514	0.2953	0.4857	0.0602	0.0754	0.0964
Telecommunication Services	6	48911	0.2213	0.3640	0.2100	0.3455	0.0230	0.0289	0.0343
Transportation	10	38521	0.2877	0.4732	0.1482	0.2438	0.0299	0.0375	0.0451
Utilities	10	16933	0.2296	0.3777	0.1237	0.2035	0.0239	0.0299	0.0351

our Technology shares is consistent with the higher VaR experienced by the Nasdaq which typically consists of high technology companies.

CVaR must always exceed VaR, as CVaR is based on the worst 5% of returns, and this is reflected in the results shown. Parametric CVaR has exactly the same ranking as VaR (CVaR is the tail end of the normal distribution). Nonparametric CVaR is the average of the actual returns beyond VaR, and tends to be slightly higher than parametric CVaR. CVaR is further discussed in Sections 6.4 to 6.5.

6.2 Industry VaR Rankings over time.

Table 2
Undiversified VaR over time - 7 year rolling windowThe table shows undiversified industry VaR for each of the nine 7 year rolling window periods.
Year 1 contains data for years 1-7. Year 2 contains data for years 2-8 and so on through to year nine which contains data for years 9-15.

Table 2 shows that most of the industries stay fairly constant over time. For example, Banks remain within a band of 0.3 to 0.36 and Energy 0.52 to 0.59. There are some industries which show higher volatility in some years, for example Telecommunication Services and Consumer Durables & Apparel show more volatility in earlier years, whilst Commercial Services & Supplies and Pharmaceuticals & Biotechnology show more volatility in latter years. There is no particular window which stands out as having a much higher or lower volatility than other years. In fact there is a very narrow range between the lowest weighted average volatility in year 1 (0.45) and the highest in year 7 (0.50). Overall, industry VaR rankings show a significant association over time. We also tested diversified VaR over time. Again, the rankings are found to be significantly constant over time.The seven year rolling window approach shown in Table 2 could be a key factor in influencing the stability in VaR over time, as there is overlap on the data with this approach. Year 1 of the rolling window approach contains 6 of the same years as year 2, year 2 contains 6 of the same years as year 3 and so on. To assess the impact of this, the table below tests historical VaR using only 1 year periods, i.e. each year contains only the last 12 months data.

Industry	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9
Automobiles & Components	0.5417	0.5232	0.5076	0.5084	0.5113	0.4772	0.4745	0.4603	0.4453
Banks	0.3030	0.3206	0.3421	0.3622	0.3646	0.3554	0.3525	0.3452	0.3384
Capital Goods	0.4591	0.4639	0.4821	0.4965	0.4826	0.4782	0.5614	0.4970	0.4949
Chemicals	0.4215	0.4263	0.4090	0.4365	0.4599	0.4585	0.4346	0.4272	0.4273
Commercial Services & Supplies	0.5380	0.5291	0.5763	0.6012	0.5591	0.5074	0.4981	0.4448	0.4355
Construction Materials	0.4424	0.4251	0.4403	0.4587	0.5162	0.4924	0.4975	0.5100	0.4895
Consumer Durables & Apparel	0.5294	0.5593	0.6159	0.6702	0.6498	0.6767	0.4630	0.6997	0.6425
Diversified Financials	0.4145	0.4273	0.4453	0.4801	0.4871	0.4855	0.5462	0.5382	0.4706
Energy	0.5904	0.5904	0.5921	0.5689	0.5608	0.5567	0.5419	0.5520	0.5241
Food & Staples Retailing	0.3727	0.3943	0.4150	0.4361	0.4351	0.4277	0.3722	0.3634	0.3526
Food Beverage & Tobacco	0.3987	0.4548	0.5221	0.5823	0.5532	0.5233	0.5476	0.5183	0.4937
Healthcare Equipment & Services	0.5246	0.5618	0.6075	0.6302	0.6007	0.5992	0.5862	0.5613	0.4938
Hotels Restaurants & Leisure	0.5147	0.5517	0.5043	0.4855	0.4855	0.5138	0.5290	0.5397	0.4056
Insurance	0.5366	0.5392	0.5625	0.5650	0.4989	0.4531	0.4777	0.4440	0.5393
Media	0.4561	0.4676	0.4911	0.4895	0.4711	0.4640	0.5406	0.4720	0.4378
Metals & Mining	0.5595	0.5568	0.5829	0.5812	0.5671	0.5362	0.5900	0.5401	0.5351
Paper & Forest Products	0.6713	0.6612	0.6220	0.5584	0.5256	0.5381	0.5485	0.6531	0.5321
Pharmaceuticals & Biotechnology	0.6729	0.7437	0.8295	0.9552	0.8073	0.6368	0.7123	0.6631	0.5726
Real Estate	0.3931	0.4139	0.4195	0.4179	0.4100	0.4012	0.4295	0.3958	0.3878
Retailing	0.5077	0.4964	0.4578	0.5432	0.5349	0.5144	0.4762	0.4439	0.4273
Software & Services	0.8412	0.9098	0.9515	1.0290	0.9316	0.8245	1.4855	1.5071	0.8393
Technology Hardware & Equipment	0.9514	0.8861	0.9342	0.9973	0.9813	0.9356	0.8689	0.8363	0.7758
Telecommunication Services	0.3640	0.3821	0.4584	0.4925	0.5090	0.5477	0.7407	0.6555	0.7328
Transportation	0.4732	0.4828	0.4879	0.5184	0.5352	0.4991	0.4628	0.4289	0.4233
Utilities	0.3777	0.3834	0.3948	0.4261	0.4390	0.4622	0.4803	0.4929	0.4561
Weighted Average	0.4516	0.4634	0.4851	0.4990	0.4891	0.4724	0.5023	0.4767	0.4624
degrees of freedom	8								
K	5.56								
critical value	15.51								
association significant at 95% level?	y								

Table 3
Historical VaR using 12 month data windows

Industry	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9
Automobiles & Components	0.5660	0.5956	0.3913	0.4227	0.5943	0.5276	0.5440	0.4515	0.5093
Banks	0.2439	0.2231	0.2387	0.3163	0.3506	0.3588	0.3620	0.3709	0.3785
Capital Goods	0.3787	0.3775	0.3711	0.4980	0.4816	0.5460	0.5896	0.4580	0.4932
Chemicals	0.4000	0.4106	0.3030	0.4108	0.5324	0.4911	0.4606	0.4107	0.4515
Commercial Services & Supplies	0.4307	0.4084	0.4386	0.6297	0.5698	0.5393	0.5973	0.4648	0.4986
Construction Materials	0.4804	0.3855	0.3992	0.3938	0.5390	0.5096	0.5342	0.5718	0.5968
Consumer Durables & Apparel	0.4278	0.4819	0.3696	0.6513	0.6302	0.6748	0.4603	0.5344	0.5733
Diversified Financials	0.4126	0.3434	0.3004	0.3842	0.4190	0.3782	0.5238	0.5093	0.4850
Energy	0.5647	0.5411	0.4356	0.4795	0.4911	0.5356	0.6188	0.5970	0.5617
Food & Staples Retailing	0.2886	0.2919	0.2382	0.3359	0.4519	0.4923	0.4114	0.3951	0.4072
Food Beverage & Tobacco	0.3554	0.3490	0.2842	0.3503	0.3728	0.4576	0.5026	0.5636	0.6597
Healthcare Equipment & Services	0.4614	0.4405	0.4601	0.5392	0.6170	0.5719	0.5830	0.5679	0.5129
Hotels Restaurants & Leisure	0.3567	0.4369	0.4212	0.4873	0.4446	0.4740	0.5937	0.6012	0.4261
Insurance	0.3493	0.3566	0.4143	0.5542	0.6270	0.4051	0.5228	0.3938	0.5728
Media	0.3545	0.3514	0.3411	0.4357	0.4415	0.4612	0.6577	0.4856	0.4311
Metals & Mining	0.5730	0.4394	0.4641	0.4957	0.6042	0.5218	0.6255	0.6545	0.6709
Paper & Forest Products	0.5372	0.5809	0.4705	0.3982	0.4824	0.6036	0.6015	0.6815	0.5770
Pharmaceuticals & Biotechnology	0.5491	0.5847	0.5905	0.9098	0.8307	0.7079	0.8229	0.8008	0.5872
Real Estate	0.2823	0.2945	0.2904	0.3374	0.3587	0.4495	0.4622	0.4270	0.4312
Retailing	0.4948	0.4515	0.3715	0.5082	0.5835	0.5670	0.6035	0.5276	0.4845
Software & Services	0.5257	0.6471	0.5947	0.8394	0.9397	0.8152	1.2598	1.6003	0.8830
Technology Hardware & Equipment	0.8440	0.6526	0.7582	1.1482	1.2236	1.2408	1.0945	0.9587	0.8250
Telecommunication Services	0.3355	0.2447	0.2563	0.3352	0.3783	0.4965	0.8259	0.5483	0.7500
Transportation	0.4009	0.4037	0.3366	0.4893	0.5449	0.5948	0.5507	0.4445	0.4458
Utilities	0.3556	0.3457	0.3028	0.3527	0.3954	0.4883	0.5498	0.4952	0.4774
Weighted Average	0.3943	0.3580	0.3507	0.4297	0.4780	0.4734	0.5394	0.5091	0.5187
degrees of freedom	8								
K	51.47								
critical value	15.51								
association significant at 95% level?	n								

We now see a greater variance in VaR over time. For example Banks, which had a very narrow VaR range over time, now show a range from 22% in year 2 to 38% in year 9. The weighted portfolio average is 35% in year 3 compared to 54% in year 7. We also see some changes to the ranking order. For example, on the 7 year approach, Chemicals in year 5 had a more favourable VaR than Capital Goods and in year 7 Media had a more favourable VaR than metals. These positions are reversed under the 1 year approach.

There is no significant association in rankings using 1 year windows. The fact that the 7 year window approach gives a different outcome to the 1 year approach has significant implications for users of VaR methodology such as Banks. Whilst using longer periods of data has some advantages, such as taking account of different business cycles, it is also important to focus on the more current risks. It is therefore important to consider both short and long periods, and also to use CVaR, to focus on extreme risks.

6.3 Association between diversified VaR and undiversified VaR.

Table 4 shows there is an across the board noticeable reduction in risk when correlation is applied to each industry. There is also a shift in rankings. For example, Telecommunications has a low risk ranking on an undiversified basis, but shows very little reduction in risk through diversification and thus has a higher risk ranking on a diversified basis. Other industries have risk reduction through diversification which approximates the overall portfolio average reduction, and thus retain a similar ranking on a diversified basis (for example Insurance, Paper & Forest Products, and the Technology sectors). However, our testing finds these differences not to be significant. We find significant association between diversified and undiversified VaR.

Table 4
Undiversified VaR compared to Diversified VaR
The table compares undiversified (weighted average)
VaR to diversified (correlated) VaR.
Rankings are shown in column 2,
with a ranking of 1 being the highest risk
and 25 the lowest. Column 3 shows the squared ranking
difference between undiversified and diversified VaR.
This is an indicator of the strength of differences between undiversified
and diversified rankings, with lower scores showing lesser ranking
differences,
and is an input into our significance calculation.

Industry	Values: Undiversified VaR	Values: Diversified VaR	Ranking: Undiversified VaR	Ranking: Diversified VaR	Difference in Ranks^2
Automobiles & Components	0.5417	0.3010	7	12	25
Banks	0.3030	0.2231	25	21	16
Capital Goods	0.4591	0.2369	15	18	9
Chemicals	0.4215	0.3106	18	11	49
Commercial Services & Supplies	0.5380	0.2424	8	17	81
Construction Materials	0.4424	0.3196	17	9	64
Consumer Durables & Apparel	0.5294	0.3901	10	3	49
Diversified Financials	0.4145	0.2008	19	24	25
Energy	0.5904	0.2858	5	13	64
Food & Staples Retailing	0.3727	0.2459	23	15	64
Food Beverage & Tobacco	0.3987	0.2022	20	23	9
Healthcare Equipment & Services	0.5246	0.2273	11	20	81
Hotels Restaurants & Leisure	0.5147	0.3148	12	10	4
Insurance	0.5366	0.3376	9	8	1
Media	0.4561	0.2317	16	19	9
Metals & Mining	0.5595	0.3382	6	7	1
Paper & Forest Products	0.6713	0.3612	4	5	1
Pharmaceuticals & Biotechnology	0.6729	0.3721	3	4	1
Real Estate	0.3931	0.1850	21	25	16
Retailing	0.5077	0.2821	13	14	1
Software & Services	0.8412	0.4353	2	2	0
Technology Hardware & Equipment	0.9514	0.4857	1	1	0
Telecommunication Services	0.3640	0.3455	24	6	324
Transportation	0.4732	0.2438	14	16	4
Utilities	0.3777	0.2035	22	22	0
					898
				n	25
				r	0.655
				t	4.153
				criticalvalue	2.048
				association significant at 95% level?	y

Table 5
High Level Sector Diversified VaR

Industry	VaR	Ranking
Information Technology	0.4444	1
Telecommunication Services	0.3455	2
Materials	0.3356	3
Healthcare	0.3017	4
Energy	0.2858	5
Consumer Discretionary	0.2749	6
Industrials	0.2413	7
Consumer staples	0.2294	8
Financials	0.2257	9
Utilities	0.2035	10
Weighted average	0.2675	

The table condenses the diversified industries into their higher level sectors (refer Appendix 1 for composition of these sectors).

When using higher level Sectors, Information Technology, Telecommunication Services and Materials show the highest risk, with Utilities, Financials and Consumer Staples being the lowest risk.

6.4 Association between VaR industry rankings and CVaR industry rankings.

As shown in Table 6, there are some differences in VaR and CVaR rankings which would not be apparent with a parametric approach. For example extreme activity in industries such as Hotels Restaurants & Leisure, Insurance, and Metals & Mining clearly does not follow a standard tail distribution. But in the main, most industries have similar VaR and CVaR rankings and our testing finds significant association between them.

Table 6

VaR compared to CVaR

Comparing VaR to parametric CVaR will not provide any benefit, as CVaR industry rankings are exactly the same as VaR, due to CVaR being is the tail of the normal distribution. We have therefore used nonparametric

CVaR (average of actual returns beyond VaR) to highlight the actual extreme risk.

6.5 Industry CVaR rankings over time.

Table 7

Historical daily nonparametric CVaR

The table shows undiversified industry CVaR for each of the nine 7 year rolling window periods. This is the weighted average of the actual daily returns beyond VaR. Year 1 contains data for years 1-7. Year 2 contains data for years 2-8 and so on through to year nine which contains data for years 9-15.

The overall portfolio shows a fairly narrow CVaR range from 4.21% to 4.80%. Some of the individual industries, however, show more volatility. For example, Consumer Durables and Apparel ranges from 4.22% to 7.07%, indicating some extreme events in year 8. The same applies to Pharmaceuticals & Biotechnology with a range from 5.43% to 9.52%, with the extreme events occurring in year 4. Software & Services shows a spike to 17.61% in year 7 and 18.37% in year 8. We note that in these industries, the worst years for CVaR correspond with the worst years for VaR.

These differences over time are not found to be significant and we find CVaR to be significantly constant over time.

7 Sector Indices

Besides just using risk measurements for capital adequacy purposes, Banks use them for a number of other purposes such as risk concentration limits and setting policies. Banks have traditionally obtained this industry information through their own or external macroeconomic research. The VaR and CVaR measurements we have provided can assist Banks in this process by being able to identify the relative risk of Australian industries, or they can use

Industry	Values: Undiversified Daily VaR	Values: Nonparametric CVaR	Rank: Undiversified Daily VaR	Rank: Nonparametric CVaR	Difference in Ranks^2
Automobiles & Components	0.0343	0.0536	7	7	0
Banks	0.0192	0.0268	25	25	0
Capital Goods	0.0290	0.0428	15	15	0
Chemicals	0.0267	0.0396	18	17	1
Commercial Services & Supplies	0.0340	0.0530	8	8	0
Construction Materials	0.0280	0.0390	17	19	4
Consumer Durables & Apparel	0.0335	0.0506	10	10	0
Diversified Financials	0.0262	0.0392	19	18	1
Energy	0.0373	0.0538	5	6	1
Food & Staples Retailing	0.0236	0.0343	23	24	1
Food Beverage & Tobacco	0.0252	0.0369	20	21	1
Healthcare Equipment & Services	0.0332	0.0499	11	11	0
Hotels Restaurants & Leisure	0.0326	0.0510	12	9	9
Insurance	0.0339	0.0586	9	5	16
Media	0.0288	0.0417	16	16	0
Metals & Mining	0.0354	0.0498	6	12	36
Paper & Forest Products	0.0425	0.0653	4	4	0
Pharmaceuticals & Biotechnology	0.0426	0.0656	3	3	0
Real Estate	0.0249	0.0381	21	20	1
Retailing	0.0321	0.0469	13	13	0
Software & Services	0.0532	0.0862	2	2	0
Technology Hardware & Equipment	0.0602	0.0964	1	1	0
Telecommunication Services	0.0230	0.0343	24	23	1
Transportation	0.0299	0.0451	14	14	0
Utilities	0.0239	0.0351	22	22	0
					72
				n	25
				r	0.972
				t	19.953
				criticalvalue	2.048
				association significant at 95% level?	y

Industry	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9
Automobiles & Components	0.0536	0.0525	0.0503	0.0495	0.0499	0.0450	0.0449	0.0428	0.0418
Banks	0.0268	0.0280	0.0293	0.0312	0.0316	0.0309	0.0306	0.0302	0.0299
Capital Goods	0.0428	0.0432	0.0450	0.0462	0.0445	0.0439	0.0533	0.0467	0.0472
Chemicals	0.0396	0.0402	0.0382	0.0413	0.0440	0.0441	0.0420	0.0435	0.0456
Commercial Services & Supplies	0.0530	0.0516	0.0568	0.0586	0.0532	0.0489	0.0468	0.0408	0.0400
Construction Materials	0.0390	0.0377	0.0400	0.0406	0.0466	0.0447	0.0449	0.0458	0.0442
Consumer Durables & Apparel	0.0506	0.0542	0.0593	0.0663	0.0593	0.0618	0.0422	0.0707	0.0648
Diversified Financials	0.0392	0.0407	0.0433	0.0467	0.0501	0.0496	0.0569	0.0560	0.0489
Energy	0.0538	0.0539	0.0543	0.0518	0.0519	0.0516	0.0488	0.0501	0.0468
Food & Staples Retailing	0.0343	0.0360	0.0381	0.0398	0.0396	0.0381	0.0327	0.0321	0.0311
Food Beverage & Tobacco	0.0369	0.0433	0.0500	0.0605	0.0556	0.0509	0.0551	0.0497	0.0466
Healthcare Equipment & Services	0.0499	0.0540	0.0576	0.0604	0.0580	0.0577	0.0563	0.0540	0.0470
Hotels Restaurants & Leisure	0.0510	0.0463	0.0471	0.0439	0.0438	0.0465	0.0483	0.0504	0.0363
Insurance	0.0586	0.0577	0.0592	0.0594	0.0490	0.0405	0.0422	0.0389	0.0505
Media	0.0417	0.0430	0.0451	0.0450	0.0431	0.0435	0.0509	0.0444	0.0431
Metals & Mining	0.0498	0.0500	0.0521	0.0519	0.0507	0.0481	0.0540	0.0496	0.0500
Paper & Forest Products	0.0653	0.0648	0.0606	0.0545	0.0497	0.0514	0.0489	0.0803	0.0538
Pharmaceuticals & Biotechnology	0.0656	0.0747	0.0817	0.0952	0.0787	0.0614	0.0692	0.0636	0.0543
Real Estate	0.0381	0.0395	0.0416	0.0406	0.0393	0.0380	0.0403	0.0373	0.0366
Retailing	0.0469	0.0470	0.0425	0.0510	0.0502	0.0480	0.0455	0.0434	0.0430
Software & Services	0.0862	0.0926	0.0978	0.1067	0.0928	0.0842	0.1761	0.1837	0.0889
Technology Hardware & Equipment	0.0964	0.0859	0.0908	0.0987	0.0987	0.0943	0.0865	0.0809	0.0738
Telecommunication Services	0.0343	0.0353	0.0414	0.0449	0.0474	0.0523	0.0772	0.0729	0.1830
Transportation	0.0451	0.0458	0.0450	0.0479	0.0514	0.0471	0.0423	0.0386	0.0381
Utilities	0.0351	0.0358	0.0357	0.0396	0.0392	0.0413	0.0427	0.0438	0.0399
Weighted Average	0.0421	0.0430	0.0450	0.0464	0.0453	0.0435	0.0469	0.0449	0.0480
degrees of freedom	8								
K	1.41								
critical value	15.51								
association significant at 95% level?	y								

the methodology to derive their own measurements. Banks often group risk measurements into categories (such as high, medium, low) for purposes of simplicity. For example, lower concentration limits may be allowed for a low risk industry than for a low risk one. Banks could use the actual VaR / CVaR measurements which we have provided. Alternatively risk indices could be used, or risk categories (high, low, etc). In Table 8, we provide for all of these options.

Table 8 Risk Measurements, indices and categories

The first column shows the industry. The second column shows the diversified VaR values which we have already calculated. The third column, the industry risk index, shows the relative risk of each industry to the mean, where 1 = average risk, >1 = higher than average risk and <1 = lower than average risk. The measurement is obtained by industry VaR divided by portfolio mean VaR. This measurement is useful in that it is very easy to tell the relative risk from the measurement (for example a measurement of 0.5 is an industry with half the average risk, and 2 is double the average). It also facilitates comparison between models and comparison between VaR and CVaR (if all of these have a relative index calculated). In column 3 we show the relative risk in categories of low (20th percentile), medium-low ($>$20th to 40th percentile), medium $>$40th - 60th percentile, medium-high ($>$60th – 80th percentile) and high ($>$80th percentile).

8 Conclusions

The objectives of the study were to provide market industry VaR and CVaR measurements, to compare VaR and CVaR rankings between industries over time, to compare diversified (correlated) and undiversified industry VaR rankings, and to compare parametric and nonparametric CVaR rankings for each industry. We find the Technology Sectors to show the highest risk, and lowest risk in the Financial and Utility Sectors. Although some industries show differences between diversified and undiversified risk (such as Telecommunications showing a much higher risk ranking on a diversified basis), overall there is found to be significant association between diversified and undiversified VaR.

Industry	Var			CVar			Combined Risk Category
	Daily Diversified Portfolio 95% VaR	Industry VaR Index	Var Risk Category	CVaR	Industry CVaR Index	CVaR Risk Category	
Food Beverage & Tobacco	0.0128	0.69	Low	0.0369	0.75	Low	low
Utilities	0.0129	0.69	Low	0.0351	0.71	Low	low
Banks	0.0141	0.76	Low	0.0268	0.54	Low	low
Real Estate	0.0117	0.63	Low	0.0381	0.77	Medium-Low	medium-low
Diversified Financials	0.0127	0.69	Low	0.0392	0.79	Medium-Low	medium-low
Media	0.0147	0.79	Medium-Low	0.0417	0.85	Medium-Low	medium-low
Healthcare Equipment & Services	0.0144	0.78	Medium-Low	0.0499	1.01	Medium	medium
Capital Goods	0.0150	0.81	Medium-Low	0.0428	0.87	Medium	medium
Transportation	0.0154	0.83	Medium-Low	0.0451	0.91	Medium	medium
Food & Staples Retailing	0.0156	0.84	Medium	0.0343	0.69	Low	medium
Retailing	0.0178	0.96	Medium	0.0469	0.95	Medium	medium
Chemicals	0.0196	1.06	Medium	0.0396	0.80	Medium-Low	medium
Commercial Services & Supplies	0.0153	0.83	Medium-Low	0.0530	1.07	Medium-High	medium-high
Energy	0.0181	0.98	Medium	0.0538	1.09	Medium-High	medium-high
Automobiles & Components	0.0190	1.03	Medium	0.0536	1.09	Medium-High	medium-high
Hotels Restaurants & Leisure	0.0199	1.07	Medium-High	0.0510	1.03	Medium-High	medium-high
Construction Materials	0.0202	1.09	Medium-High	0.0390	0.79	Medium-Low	medium-high
Metals & Mining	0.0214	1.15	Medium-High	0.0498	1.01	Medium	medium-high
Telecommunication Services	0.0219	1.18	Medium-High	0.0343	0.70	Low	medium-high
Insurance	0.0214	1.15	Medium-High	0.0586	1.19	High	high
Paper & Forest Products	0.0228	1.23	High	0.0653	1.32	High	high
Pharmaceuticals & Biotechnology	0.0235	1.27	High	0.0656	1.33	High	high
Consumer Durables & Apparel	0.0247	1.33	High	0.0506	1.03	Medium-High	high
Software & Services	0.0275	1.49	High	0.0862	1.75	High	high
Technology Hardware & Equipment	0.0307	1.66	High	0.0964	1.95	High	high

CVaR identifies extreme risk. There are some ranking differences between VaR and (nonparametric) CVaR, such as Insurance showing a relatively higher CVaR than VaR, but overall CVaR rankings show significant similarities to VaR rankings. There is also found to be significant association between parametric and nonparametric CVaR. There is found to be significant ranking correlation over time for both VaR and CVaR using our 7 year rolling window approach. When 1 year data frames are used, no association over time was found. This highlights the importance of using both short and long time frames in order to cover different economic cycles as well as consider current conditions. With the increased momentum in risk modelling brought about by the Basel II Accord, and the relative lack of VaR and CVaR studies in Australia, there is significant scope for additional studies on this topic, particularly with regards to CVaR, for both market and credit risk. The examination of credit VaR and CVaR in an Australian context will be discussed by the same authors in a separate paper.

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Appendix 1
Sector Breakdown – ASX

Sector	Sub sectors
Energy	Oil & Gas, Energy Equipment & Services
Materials	Metals & Mining, Construction Materials, Chemicals, Paper & Forest Products, Containers & Packaging
Industrials	Transportation, Capital Goods, Commercial Services & Supplies
Consumer Discretionary	Media, Hotels Restaurants & Leisure, Retailing, Consumer Durables & Apparel, Automobile & Components
Consumer Staples	Food Beverage & Tobacco, Food & Staples Retailing, Household & Personal Products
Health Care	Equipment & Services, Pharmaceuticals & Biotechnology
Financials	Banks, Real Estate, Diversified Financials, Insurance
Information Technology	Software & Services, Technology & Equipment, Semiconductors & Semiconductor Equipment
Telecommunications Services	Diversified, Wireless
Utilities	Gas, Electric, Multi, Water

(Australian Stock Exchange, 2006, p.1)

Appendix 1
All Ords Market Capitalisation

Industry	Market capitalisation	% of Total
Automobiles & Components	940	0.08%
Banks	238,684	19.45%
Capital Goods	29,655	2.42%
Chemicals	11,481	0.94%
Commercial Services & Supplies	30,875	2.52%
Containers & Packaging	6,134	0.50%
Construction Materials	26,321	2.15%
Consumer Durables & Apparel	4,301	0.35%
Diversified Consumer Services	1,132	0.09%
Diversified Financials	54,062	4.41%
Energy	80,045	6.52%
Food & Staples Retailing	44,120	3.60%
Food Beverage & Tobacco	29,569	2.41%
Healthcare Equipment & Services	20,550	1.67%
Hotels Restaurants & Leisure	20,165	1.64%
Insurance	60,010	4.89%
Media	33,510	2.73%
Metals & Mining	210,929	17.19%
Paper & Forest Products	5,373	0.44%
Pharmaceuticals & Biotechnology	18,659	1.52%
Real Estate	128,718	10.49%
Retailing	10,839	0.88%
Software & Services	8,845	0.72%
Technology Hardware & Equipment	1,944	0.16%
Telecommunication Services	91,567	7.46%
Transportation	38,521	3.14%
Utilities	20,082	1.64%
	1,227,031	

(Data obtained from Datastream as at June 2006 and aligned to GICS codes)